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Force analysis of bearings on a modified mechanism using proposed recurrent hybrid neural networks

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Abstract

Due to different load conditions on four-bar mechanisms, it is necessary to analyze force distribution on the bearing systems of mechanisms. A proposed neural network was developed and designed to analyze force distribution on the bearings of a four bar mechanism. The proposed neural network has three layers: input layer, output layer and hidden layer. The hidden layer consists of a recurrent structure to keep dynamic memory for later use. The mechanism is an extended version of a four-bar mechanism. Two elements, spring and viscous, are employed to overcome big force problem on the bearings of the mechanism. The results of the proposed neural network give superior performance for analyzing the forces on the bearings of the four-bar mechanism undergoing big forces and high repetitive motion tracking. This continuation of simulation analysis of bearings should be a benefit to bearing designers and researchers of such mechanisms.

Keywords: Ball bearing; Neural network; Four-bar mechanism; Ball bearing forces

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1. Introduction

Bearing force analysis of four-bar mechanisms is an important field in which mechanical engineers study motion in order to design mechanisms to perform useful tasks.

Recently, an analytical formulation for computing kinematic sensitivity of the spatial four-bar mechanism has been described in [1]. An experimental code developed was used to compute an assembled configuration for the mechanism that accounts for the effect of a design variation. A mechanism was modelled by using graph theory, in which a body is defined as a node and a kinematic joint is defined as an edge. The spherical joint was cut to convert the model into a tree structure by cutting an edge and introducing constraints. The effect of variation in mechanism design using concepts of virtual displacement and rotation was introduced. The variation of the spherical constraint was computed, maintaining joint-attachment vectors and orientation matrices as variables. A method for stability analysis of a closed-loop flexible mechanism by using modal coordinates has been investigated [2]. In their paper, mode shapes of a flexible four-bar mechanism are defined as those of individual links (single-link modes). Based on these single-link modes, the flexible four-bar mechanism has time-invariant mode shapes and its governing equations of motion become decoupled, regardless of mode-crossing. Therefore, the stability of the flexible mechanism can be analyzed efficiently for each mode. Floquet theory is employed to check the stability of the mechanism. The experimental study of a flexible four-bar mechanism is also presented to verify the proposed method. The experimentally determined bending strains and critical speeds are compared with numerical results obtained from the proposed method. The experimental and analytical results show fairly good agreement.

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A study was performed to model, simulate and control a four-bar mechanism driven by a brushless servo motor [3]. A mathematical model for the servo motor-mechanism system was developed and solved by using numerical methods. An experimental set-up based on a four-bar mechanism was built and different crank motion profiles were implemented. Simulation and experimental results were then presented, compared and discussed.

An experimental investigation an active control of the elastodynamic response of a four-bar (4R) mechanism has been presented by Sannah and Smaili [4]. In their research, an experimental 4R mechanism is made such that its coupler link is flexible, its follower link is slightly less flexible and its crank is relatively rigid, two thin plate-type piezoceramic S/A pairs were bonded to the flanks of the coupler link at the high strain locations corresponding to the first and second vibration modes. The results of the experimental investigation prove that in order to prevent high mode excitations, the controller design should be based on the modes representing vibrations of all components comprising the mechanism system rather than the modes corresponding to the link to which the S/A pairs were bonded.

A neural network based application has been employed to predict vertical vibration parameters of vehicles [5]. The method was used to predict random vibration theory results. In their investigation, the results have demonstrated the applicability and adaptability of the neural network for analysis of the vehicles vibrations.

In this paper, a hybrid type neural network approach for analyzing forces on a four-bar mechanism's bearings is presented to predict and improve in early design stage. A proposed neural network is employed to predict forces of bearing for the analyzed mechanism's fault detection.

The paper is organized as follows: the bearing mechanism structure is explained in Section 2. Section 3 presents the proposed neural network theory. Simulation results with the proposed neural network for mechanism joints bearing forces are given in Section 4. The paper is concluded with Section 5.

2. Modified four-bar mechanism

The four-bar mechanism is a glass of mechanical linkage in which four links are pinned together with bearings to form a closed loop in order to perform some useful motion. Because the shapes of paths created by coupler are so diverse and useful, the four-bar mechanism with ball bearings is used in industry numerous applications that require generation of simple repetitive movements.

The bearing mechanism, which operates in a vertical plane, is shown schematically in Fig. 1. The system can be used as a five-bar mechanism with a rotary input at OA used an oscillatory input at CD, or, as in this case, as a four-bar linkage with the link CD fixed. The crank, OA, is driven by a variable speed motor and a spring of stiffness 671 N/m is attached to the rocker link, BC, to provide additional loading to the mechanism. A test bearing at B has a radial clearance of 100 μm and consists of a steel pin with an oil-impregnated sintered bronze bush, of nominal diameter 25 mm and 35 mm long. Two small shock accelerometers are attached to the test bearing to record the impact accelerations at B along and perpendicular to the direction AB.

The crank speed is a periodic function of the crank angle, due to the cyclic variation of the gravitational and dynamic forces on the mechanism, and the crank motion can be expressed either as an average crank speed or as an instantaneous speed relative to a specified crank angle. All crank speeds quoted in this paper are instantaneous values at $\theta_2=90^0$ crank angle.

The average crank speed is used in the range 200-400 r/min and the outputs from the shock accelerometers are monitored.

In the combined massless-link-spring-damper model the clearance bearing, B, is presented by a masless link BC of length equal to radial clearance, r_4. BC has radial stiffness, K_c, and a radial damping μ_c.

The equations of motion for the model are given in Appendix A. There are six kinematic equations and

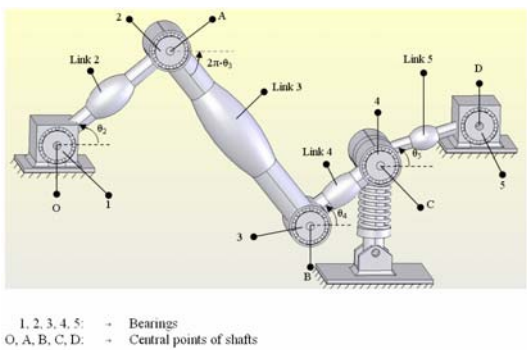


Fig. 1. Representation of the ball bearing mechanism.

Table 1. Structural and training parameters of the proposed neural network.

NN	η	μ	α	β	n	N	AF
RHNN	0.0001	0.01	0.8	0.8	12+12	35000	HT

η: Learning rate
μ: Momentum term
α: Feedback gain from output layer to hidden layer
β: Feedback gain from hidden layer to itself
n: number of neurons in hidden layer
N: Iteration numbers
AF: Activation function
RHNN: Recurrent Hybrid Neural Network
HT. Hyperbolic Tangent

six dynamic equations. The equations are coupled, non-linear and, having no analytical solution, need to be integrated numerically. The numerical values for the model parameters used in the computations are given in Table 1.

3. Neural networks

Neural networks (NNs) are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output. Most NNs contain some form of 'learning rule' which modifies the weights of the connections according to the input patterns that it is presented with. In a sense, NNs learn by example, as do their biological counterparts: a child learns to recognize dogs from examples of dogs. Although there are many different kinds of learning rules used by neural networks, this demonstration is concerned only with one: the delta rule. The delta rule is often utilized by the most common class of NNs called 'backpropagational neural networks' (BPNNs). BP is an abbreviation for the backwards propagation of error. With the delta rule, as with other types of BP, 'learning' is a supervised process that occurs with each cycle or 'epoch' (i.e., each time the network is presented with a new input pattern) through a forward activation flow of outputs, and the backwards error propagation of weight adjustments. More simply, when a neural network is initially presented with a pattern it makes a random 'guess' as to what it might be. It then sees how far its answer was from the actual one and makes an appropriate adjustment to its connection weights. Backpropagation performs a gradient descent within the solution's vector space towards a 'global minimum' along the steepest vector of the error surface. The global minimum is that theoretical solution with the lowest possible error. The error surface itself is a hyperparaboloid but is seldom 'smooth' as is depicted in the graphic below. Indeed, in most problems, the solution space is quite irregular with numerous 'pits' and 'hills' which may cause the network to settle down in a 'local minimum' which is not the best overall solution. Since the nature of the error space cannot be known a priori, neural network analysis often requires a large number of individual runs to determine the best solution. Most learning rules have built-in mathematical terms to assist in this process which control the 'speed' (Beta-coefficient) and the 'momentum' of the learning. The speed of learning is actually the rate of convergence between the current solution and the global minimum. Momentum helps the network to overcome obstacles (local minima) in the error surface and settle down at or near the global minimum.

Depending on the nature of the application and the strength of the internal data patterns, one can generally expect a network to train quite well. This applies to problems where the relationships may be quite dynamic or non-linear. NNs provide an analytical alternative to conventional techniques which are often limited by strict assumptions of normality, linearity, variable independence etc. Because an NN can capture many kinds of relationships it allows the user to quickly and relatively easily model phenomena which otherwise may have been very difficult or impossible to explain otherwise.

3.1 Proposed neural network model

The neural networks employed in this work were of the recurrent type. Recurrent networks have the advantage of being able to model dynamics systems accurately and in a compact form. A recurrent network can be represented in a general diagrammatic form as illustrated in Fig. 4. This diagram depicts the hybrid hidden layer as comprising a linear part and a non-linear part and shows that, in addition to the usual feedforward connections, the networks also have feedback connections from the output layer to the hidden layer and self-feedback connections in the hidden layer. The reason for adopting a hybrid linear/non-linear structure for the hidden layer will be

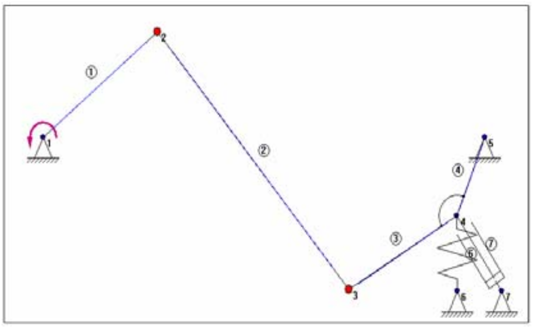


Fig. 2. Schematic representation of the extended mechanism.

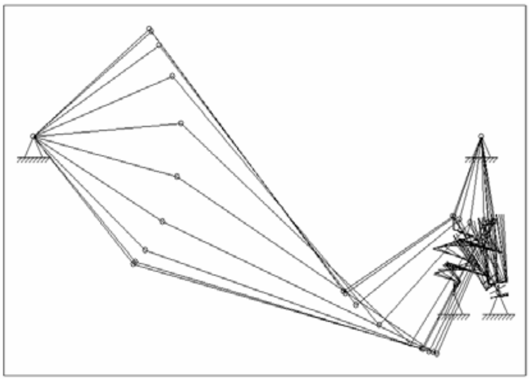


Fig. 3. Representation of the proposed mechanism during working.

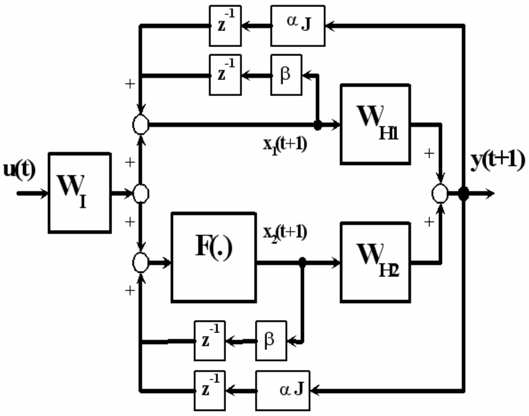


Fig. 4. Block diagram of proposed recurrent hybrid network model of the bearing system.

evident later [6, 7].

At a given discrete time t, let $\mathbf{u}(t)$ be the input to a recurrent hybrid network, $\mathbf{y}(t)$, the output of the network, $\mathbf{x}_1(t)$ the output of the linear part of the hidden layer and $\mathbf{x}_2(t)$ the output of the non-linear part of the hidden layer.

The operation of the network is summarized by the following equations (see also Fig. 4):

$$\mathbf{x}_1(t+1)=\mathbf{W}^{I1}\,\mathbf{u}(t+1)+\beta\;\mathbf{x}_1(t)+\alpha\mathbf{J}_1\mathbf{y}(t) \tag{1}$$

$$\mathbf{x}_2(t+1)=\mathbf{F}\{\mathbf{W}^{I2}\,\mathbf{u}(t+1)+\beta\;\mathbf{x}_2(t)+\alpha\mathbf{J}_2\mathbf{y}(t)\} \tag{2}$$

$$\mathbf{y}(t+1)=\mathbf{W}^{H1}\,\mathbf{x}_1(t+1)+\mathbf{W}^{H2}\,\mathbf{x}_2(t+1) \tag{3}$$

where $\mathbf{W}^{I1}$ is the matrix of weights of connections between the input layer and the linear hidden layer, $\mathbf{W}^{I2}$ is the matrix of weights of connections between the input layer and the non-linear hidden layer, $\mathbf{W}^{H1}$ is the matrix of weights of connections between the linear hidden layer and the output layer, $\mathbf{W}^{H2}$ is the matrix of weights of connections between the non-linear hidden layer and the output layer, $\mathbf{F}\{\}$ is the activation function of neurons in the non-linear hidden layer and α and β are the weights of the self-feedback and output feedback connections. $\mathbf{J}_1$ and $\mathbf{J}_2$ are, respectively, $n_{H1}\times n_O$ and $n_{H2}\times n_O$ matrices with all elements equal to 1, where n_{H1} and n_{H2} are the numbers of linear and non-linear hidden neurons, and n_O, the number of output neurons.

If only linear activation is adopted for the hidden neurons, the above equations simplify to:

$$\mathbf{y}(t+1)=\mathbf{W}^{H1}\,\mathbf{x}(t+1) \tag{4}$$

$$\mathbf{x}(t+1)=\mathbf{W}^{I1}\,\mathbf{u}(t+1)+\beta\mathbf{x}(t)+\alpha\mathbf{J}_1\,\mathbf{y}(t) \tag{5}$$

Replacing $\mathbf{y}(t)$ by $\mathbf{W}^{H1}\,\mathbf{x}(t)$ in Eq. (5) gives

$$\mathbf{x}(t+1)=(\beta\,\mathbf{I}+\alpha\,\mathbf{J}_1\,\mathbf{W}^{H1})\mathbf{x}(t)+\mathbf{W}^{I1}\,\mathbf{u}(t+1) \tag{6}$$

where $\mathbf{I}$ is a $n_{H1}\times n_{H1}$ identity matrix

Eq. (6) is of the form

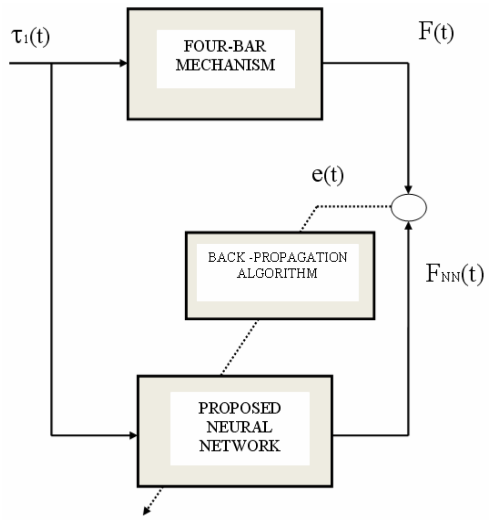
$$\mathbf{x}(t+1)=\mathbf{A}\,\mathbf{x}(t)+\mathbf{B}\,\mathbf{u}(t+1) \tag{7}$$

where $\mathbf{A}=\beta\mathbf{I}+\alpha\mathbf{J}\mathbf{W}^{H1}$ and $\mathbf{B}=\mathbf{W}^{I1}$

Eq. (7) represents the state equation of a linear system of which $\mathbf{x}$ is the state vector. The elements of $\mathbf{A}$ and $\mathbf{B}$ can be adjusted through training so that any arbitrary linear system of order n_{H1} can be modelled by the given network. When non-linear neurons are adopted, this gives the network the ability to perform non-linear dynamics mapping and thus model non-linear dynamic systems. The existence in the recurrent network of a hidden layer with both linear and non-linear neurons facilitates the modelling of practical non-linear systems comprising linear and non-linear parts.

4. Simulation results

In this section, a four-bar mechanism with a viscous and spring is chosen to be tested because it supports the idea of levels with increasing complexity of behavior in a natural way. The modelling architecture illustrated in Fig. 5 was implemented on a Pentium Core Due 2 2.00GHz PC using the proposed neural network for force analysis on bearings of a modified four-bar mechanism. Description of the neural network algorithm which was combined with the equations of motion four-bar mechanism is given in this Figure. The training and testing data set of the neural network predictor was found by modified four-bar mechanism with actuated bearing 1. On the other hand, a neural network was trained and tested with standard backpropagation algorithm. The training and structural parameters of the neural network were selected empirically for finding exact model of the four-bar mechanism. The structural and training parameters of the network are given in Table 1. Firstly, the network was randomly trained between the force values of the mechanism's joints. Kinematics and dynamics parameters of the four-bar mechanism are given in Table 2.



$\tau 1(t)$: Torque of juint 1
$F(t)$: Forces of bearings 3, 4 and 5
$F_{NN}(t)$: Forces of neural network predictor

Fig. 5. Block diagram of proposed recurrent hybrid network model combined with four-bar mechanism.

The performance of the proposed neural predictor was tested on the system for different forces of the bearings such as bearings 5, 6 and 7. The actual forces of the system's bearing 3 superimposed on the specified forces are plotted in Fig. 6. The neural predictor possesses a much faster response characteristic and therefore has better performance.

Table 2. Kinamatic Parameters of the bearing mechanism.

Parameters	Values
I_2	0.2188kg m^2
I_4	0.2094kg m^2
m_2	12.9kg
m_3	2.41kg
m_4	5.04kg
r_1	800mm
r_2	100mm
r_3	390mm
r_4	580mm
r_5	100mm
r_c	100μm
θ_5	70°

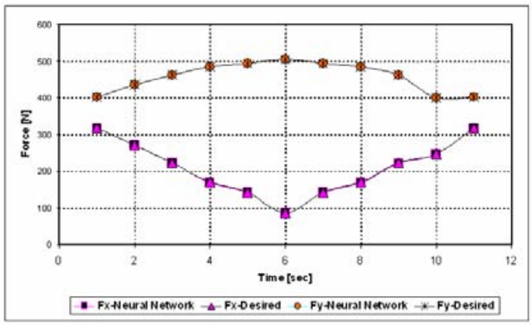


Fig. 6. Force variations of bearing 3 for both approaches in the X and Y directions.

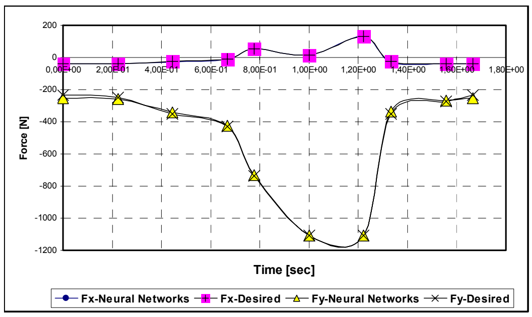


Fig. 7. Force variations of bearing 4 for both approaches in the X and Y directions.

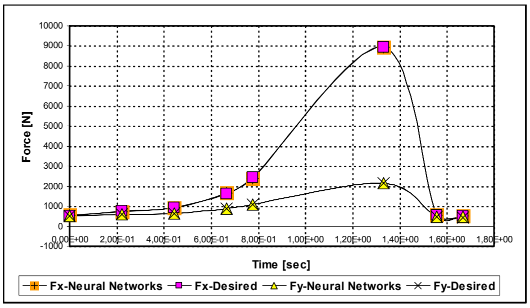


Fig. 8. Force variations of bearing 5 for both approaches in the X and Y directions.

In Fig. 7, the neural network predictor exactly follows the desired results of the system for bearing 4. There is also another analysis for bearing 5 as depicted in Fig. 8. There is good stability between two approaches.

From the results obtained, it can be seen that the proposed neural predictor produced the best performance. The advantage of the proposed predictor is faster learning and small tracking errors. A reason for the strong performance of the proposed network was the inclusion of both linear and non-linear neurons in the network. However, it can be noted from the figures and tables presented that the neural predictor for all cases was better than traditional methods.

5. Discussion and conclusion

This paper has presented a neural network predictor for analyzing forces of bearings of a modified four-bar mechanism. The main contribution of this investigation was the analysis of joint forces of the four-bar mechanism using a proposed backpropagation neural network. In this new approach, a well-trained network supplies good prediction on forces on bearings of the mechanism. The results presented were given superior performance to predict bearings forces of the proposed mechanism. The overall analysis strategy is very simple to implement since no a priori knowledge of the ball-bearing mechanism parameters is needed. Another clear advantage of this proposed neural network approach is that it was just one or two iterative variables, which helps to reduce the memory space requirements in practical applications. Finally, the proposed recurrent neural network predictor is very useful when conventional algorithms cannot properly handle in the case of large disturbances and parameters changes. Simulation results proved that the proposed neural network enables four-bar mechanisms to have a precise prediction performance. To overcome the case of large disturbances of very high sounds, vibrations and sharpness of mechanisms, an adaptive proposed neural network type was used. It can be said that the neural network would be a useful algorithm for analyzing such a mechanism's bearings in experimental work.

Nomenclature

c	:	Viscous damping coefficient
F { }	:	Activation function of neurons in non-linear hidden layer
I	:	n_{H1} x n_{H1} identity matrix
I_2	:	Inertia moment of link 2
I_4	:	Inertia moment of link 4
J_1, J_2	:	n_{H1} x n_O and n_{H2} x n_O matrices with all elements
k	:	Spring constant
K_c	:	Radial stiffness
m_2	:	Mass of link 2
m_3	:	Mass of link 3
m_4	:	Mass of link 4
n_{H1}	:	Number of neurons in hidden layer's linear part
n_{H2}	:	Number of neurons in hidden layer's non-linear part
n_O	:	Number of neurons in output layer
r	:	Radial clearance radius
r_1	:	Distance of between bearing 1 and bearing 5
r_2	:	Length of link 2
r_3	:	Length of link 3
r_4	:	Length of link 4
r_5	:	Length of link 5
u(t)	:	Input to recurrent hybrid network
W^{I1}	:	Matrix of weights of connections between input layer and hidden layer
W^{I2}	:	Matrix of weights of connections between input layer and non-linear hidden layer
W^{H1}	:	Matrix of weights of connections between linear hidden layer and output layer
W^{H2}	:	Matrix of weights of connections between non-linear hidden layer and output layer
$x_1(t)$	:	Output of linear part of hidden layer
$x_2(t)$	:	Output of non-linear part of hidden layer
y(t)	:	Output of network
θ_2	:	Rotation angle of bearing 1
θ_3	:	Rotation angle of bearing 2
θ_4	:	Rotation angle of bearing 3

θ_5 : Rotation angle of bearing 4
α and β : The weights of the self-feedback and out put feedback connections.
μ_c : Radial damping of BC link

References

[1] H. L. Zou, K. A. Abdel Malek and J. Y. Wang, A variational approach for the design of spatial four-bar mechanism, *Mechanics of Structures and Machines,* 25 (1) (1997) 41-59.

[2] K. H. Yang and Y. S. Park, Dynamic stability analysis of a flexible four-bar mechanism and its experimental investigation, *Mechanism and Machine Theory,* 33 (3) (1998) 307-320.

[3] L. C. T. Dülger and S. Uyan, Modelling, simulation and control of a four-bar mechanism with a brushless servo motor, *Mechatronics,* 7 (4) (1997) 369-383.

[4] M. Sannah and A. Smaili, Active control of elasto-dynamic vibrations of a four-bar mechanism system with a smart coupler link using optimal multivariable control: Experimental implementation, *Journal of Mechanical Design,* 120 (2) (1998) 316-326.

[5] Ş. Yıldırım and İ. Uzmay, Neural network applications to vehicle's vibration analysis, *Mechanism and Machine Theory,* 38 (2003) 27-41.

[6] Ş. Yıldırım, Robot Trajectory Control Using Neural Networks, *IEE Electronics Letters,* 38 (19) (2002) 1111-1113.

[7] Ş. Yıldırım, Design of an artificial neural network predictor for anlaysing of a hydrodynamic trust bearing system, *Industrial Lubrication and Tribology*, 58 (22) (2006) 89-94.

Appendix

Equation of motion for the model ball bearing mechanism

Kinematic equations

$$-r_1 + r_2\,Cos\theta_2 + r_3\,Cos\theta_3 + r_4\,Cos\theta_4 + r_5\,Cos\theta_5 + r_c\,Cos\theta_c = 0 \tag{8}$$

$$r_2\,Sin\theta_2 + r_3\,Sin\theta_3 + r_4\,Sin\theta_4 + r_5\,Sin\theta_5 + r_c\,Sin\theta_c = 0 \tag{9}$$

$$r_2\,\dot\theta_2\,Sin\theta_2 + r_3\,\dot\theta_3\,Sin\theta_3 + r_4\dot\theta_4\,Sin\theta_4 + r_c\dot\theta_c\,Sin\theta_c - \dot r_c\,Cos\theta_c = 0 \tag{10}$$

$$r_2\,\dot\theta_2\,Cos\theta_2 + r_3\,\dot\theta_3\,Cos\theta_3 + r_4\dot\theta_4\,Cos\theta_4 + r_c\dot\theta_c\,Cos\theta_c + \dot r_c\,Sin\theta_c = 0 \tag{11}$$

$$\begin{aligned} &r_2\,\ddot\theta_2\,Sin\theta_2 + r_3\,\ddot\theta_3\,Sin\theta_3 + r_4\ddot\theta_4\,Sin\theta_4 \\ &+ r_c\ddot\theta_c\,Sin\theta_c - \ddot r_c\,Cos\theta_c + r_2\dot\theta_2^2 Cos\theta_2 \\ &+ r_3\dot\theta_3^2 Cos\theta_3 + r_4\dot\theta_4^2 Cos\theta_4 + r_c\dot\theta_c^2 Cos\theta_c \\ &+ 2\dot r_c\dot\theta_c Sin\theta_c = 0 \end{aligned} \tag{12}$$

$$\begin{aligned} &r_2\,\ddot\theta_2\,Cos\theta_2 + r_3\,\ddot\theta_3\,Cos\theta_3 + r_4\ddot\theta_4\,Cos\theta_4 \\ &+ r_c\ddot\theta_c\,Cos\theta_c + \ddot r_c\,Sin\theta_c - r_2\dot\theta_2^2 Sin\theta_2 \\ &- r_3\dot\theta_3^2 Sin\theta_3 - r_4\dot\theta_4^2 Sin\theta_4 - r_c\dot\theta_c^2 Sin\theta_c \\ &+ 2\dot r_c\dot\theta_c Cos\theta_c = 0 \end{aligned} \tag{13}$$

Dynamic equations

For link 2:

$$X_{32} r_2 Sin\theta_2 - Y_{32} r_2 Cos\theta_2 + m_2 g s_2 Cos\theta_2 = -(I_2 + m_2 s_2^2)\ddot\theta_2 \tag{14}$$

$$X_{32} - X_{43} = m_3 r_2 \ddot\theta_2 Sin\theta_2 + m_3 s_3 \ddot\theta_3 Sin\theta_3 + m_3 r_2 \dot\theta_2^2 Cos\theta_2 + m_3 s_3 \dot\theta_3^2 Cos\theta_3 \tag{15}$$

$$X_{32} s_3 Sin\theta_3 - Y_{32} s_3 Cos\theta_3 + X_{43}(r_3 - s_3) Sin\theta_3 - Y_{43}(r_3 - s_3) Cos\theta_3 = -I_3\ddot\theta_3 \tag{16}$$

For clearance link:

$$X_{43} r_c Sin\theta_c - Y_{43} r_c Cos\theta_c = 0 \tag{17}$$

$$X_{43} Cos\theta_c + Y_{43} Sin\theta_c = K_c(r_c - r_{c0}) + \mu_c \dot r_c \tag{18}$$

For link 4:

$$Y_{43} r_4 Cos\theta_4 - X_{43} r_4 Sin\theta_4 - m_4 g(g(r_4 - s_4) Cos\theta_4 = -[I_4 + m_4(r_4 - s_4)^2]\ddot\theta_4 \tag{19}$$